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Bayesian Inversion Approach to Retrieve Soil Moisture with ERS-2 SAR Image

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ABSTRACT:
The information regarding spatial and temporal variation of soil moisture in catchments is of utmost importance in hydrological, as well as many other studies. Point measurements from gravimetric and other methods for soil moisture determination are insufficient to understand the spatial behavior of soil moisture in a region. Microwave remote sensing data from active sensors on board various satellites are increasingly being used to map spatial distribution of soil moisture within the 0–10 cm top surface. The northern part of India has a network of large rivers and canals and, therefore, spatial and temporal distribution of soil moisture in this region has a significant bearing on the hydrology of the region. In this paper, results on estimation of soil moisture from an ERS-2 SAR image in the catchment of the Solani River (a tributary to the River Ganga) in and around the town of Roorkee, India, have been presented. The radar backscatter coefficient for each pixel of the image has been modeled from the digital numbers of the SAR image. The Bayesian Approach has been made use of to then derive a relationship between the soil moisture and the radar backscatter coefficient. Finally these results have been applied to the SAR image and soil moisture has been retrieved and evaluated with ground truth observations. These results demonstrate the utilization of SAR data for estimation of spatial distribution of soil moisture in the region of the present study.

Key words: SAR, Bayesian Approach, Soil Moisture, ERS image

INTRODUCTION

Estimation of land surface parameters from imaging radar had been of interest in recent past. Estimation of soil moisture, surface roughness and vegetation parameters from satellite measurements is of primary importance for agricultural, hydrology and meteorological applications. This is because soil moisture affects many hydrological and meteorological processes at various scales. It plays a major role in regulating the interaction between the atmosphere and the land surface, and at the same time determines the distribution of precipitation into run-off and ground water storage. Therefore, it is necessary to understand and interpret the spatial distribution of soil moisture at regional as well as global scale.

A number of gravimetric methods exist by which soil moisture can be measured at select locations. However, these are point methods and cannot be used at spatial scales because soil moisture is subject to spatial and temporal variations. Therefore, for the retrieval of this information, a need exists to examine the microwave response to various surface properties. Microwave remote techniques have the ability to measure soil moisture under a variety of topographic and vegetation cover conditions quantitatively. The inversion of soil moisture information from radar backscatter became more rigorous after the availability of multi-polarization radar data. During recent years, theoretical modeling and field experiments have established the fundamentals of active microwave remote sensing as an important tool in determining physical properties of soil. The ability to estimate soil moisture in the surface layer to an approximately 5 cm depth by microwave remote sensing has been demonstrated under a variety of the topographic and land cover conditions [1-13].
Several methods i.e. mesh graph method [1] and the artificial neural network method [2], least square method [3] to retrieve the surface roughness and soil wetness have been proposed. These approaches have been proved to be applicable. Of course, for the mesh graph method the soil structure must be known in order to simulate and draw many mesh lines. The ANN method always takes the large amount of data and a long time to train the network.

The radar detects the backscatter coefficient as a result of scattering from the surface. The backscatter coefficient depends on the dielectric constant of the soil and the surface parameters like rms height, vegetation cover and the incidence angle. Dielectric constant is related to soil moisture through an empirical relation, which is a function of soil texture. Using the Bayesian approach [6], the dielectric constant can be determined as a function of the backscatter coefficient, along with minimizing the effects of vegetation and roughness. From this, the soil moisture can easily be estimated and the soil moisture map of the region can be developed, correct to a large accuracy.

STUDY AREA

The site was chosen in the Solani river catchments around Roorkee town in Uttarakhand (India) for

investigation and for monitoring surface soil moisture content. The site was a relatively flat area with elevations ranging from 245.5 meters to 289.9 meters over an area ranging from Latitude 30.51 N, Longitude 77.68 E to Latitude 29.60 N, Longitude 77.47 E. The vegetation consisted of 5 classes: barren land, grassland, sugarcane, cherry and rice. Microwave Remote Sensing image (SAR) of dates 28th July 2003 is used

METHODOLOGY FOR SOIL MOISTURE RETRIEVAL USING ERS-2 SAR IMAGE

1. Collection of field data
2. Collection of remote sensing data
3. Geo-referencing of ERS-2 SAR image
4. Computation of backscatter coefficient
5. Determination of dielectric constant using Bayesian Inversion Approach
6. Determination of Soil moisture using the Dielectric constant
7. Error analysis

Collection of field data

The first step involved the collection of field data such as soil surface roughness height and vegetation parameter measurements, as well as the volumetric soil moisture at selected locations using conventional gravimetric method. The digital numbers corresponding to these select locations were also collected.

Collection of remote sensing data

In the next step, the ERS-2 SAR C band image of the area was acquired at 5.3 GHz frequency and VV polarization at a spatial resolution of about 12.5 meters. The image was of the date 28th July 2003 and geo-referenced image is shown in Fig. 1.

Geo-referencing of ERS-2 SAR image

Geo-referencing is the process of assigning map co-ordinates to the image data and then re-sampling the pixels of the image to confirm to the map projection system. Since the SAR images are acquired in the microwave region of electromagnetic spectrum, visual identification of ground control points is very difficult. Thus, the ERS-2 SAR images have been geo-referenced to geographical co-ordinates using 5 ground control points (four at the corners and one at the center of the image). A first order polynomial transformation function and the nearest neighbor re-sampling technique have been used to perform geo-referencing. The geo-referenced image is thus obtained (Fig. 1).

Computation of backscatter coefficient

The backscatter coefficient at each sampling location of geo-referenced ERS-2 SAR image is computed using an in-house program written in MATLAB. The program is based on the algorithm proposed by European Space Agency (ESA) guidelines.

The following assumptions on the local incidence angle α are made:

- a flat terrain is considered, i.e. there is no slope. The incidence angle α is depending only on the ellipsoid and varies from about 19.5^o at near range to about 26.5^o at far range.
- any change in incidence angle across a distributed target is neglected, i.e. a distributed target corresponds to one average value of the incidence angle.

The backscattering coefficient σ^o of a distributed target is given by the following simplified equation:

$$\sigma^0 = \left(\frac{1}{N} \cdot \sum_{i,j=1}^{i,j=N} DN_{ij}^2 \right) \cdot \frac{1}{K} \frac{\operatorname{Sin}\alpha}{\operatorname{Sin}\alpha_{ref}} \tag{1}$$

- N is the number of pixels within the Area Of Interest (AOI) i.e. the group of pixels corresponding to the distributed target in the image,
- i and j are the range and azimuth locations of the pixels within the distributed target containing N pixels,
- DN_{ij} is the digital number corresponding to the pixel at location (i,j),
- α is the average incidence angle within the distributed target,
- α_{ref} is the reference incidence angle, degrees. i.e. 23^0
- k is a constant whose value depends on the image. In this case it is 889201.00 9as provided by the ESA).

If the area of interest is reduced to one pixel, then the backscatter coefficient for the pixel at location (i, j) is given by:

$$\sigma° = DN_{ij}^{2.} \sin\alpha/(k.\sin\alpha_{ref}) \tag{2}$$

Taking $\alpha = \alpha_{ref}$ we get

$$\sigma° = DN_{ij}^2/k \tag{3}$$

Therefore, from the DN values obtained from the image the backscatter values were obtained.

Determination of dielectric constant using Bayesian inversion Approach

There are different techniques available for the estimation of physical parameters of land surfaces, but the major problem associated with most of them is that the error, once crept in, takes away the accuracy of whole analysis. Error can be there because of measurement error, the non-uniformity of the background power distribution and the in homogeneity of the surface within a given resolution element or from element to the next. We have used here the Bayesian Estimation Technique, which enables us to get away with the aforementioned problems. It

provides a methodology to fine-tune the results iteratively so as to make them very accurate.

Use of Bayesian Approach to estimate backscatter coefficient

Bayesian classification is based on Bayes theorem. P(H|X) is the posterior probability, or a posteriori probability, of H conditioned on X. For example, suppose the world of data samples consists of fruits, described by their color and shape. Suppose that X is red and round, and that H is the hypothesis that X is an apple. Then P(H|X) reflects our confidence that X is an apple given that we have seen that X is red and round. In contrast, P(H) is the prior probability, or apriori probability of H. For our example, this is the probability that any given data sample is an apple, regardless of how the data sample looks. The posterior probability, P(H|X) is based on more information (such as background knowledge) than the prior probability, P(H), which is independent of X.

The inversion procedure is based on Bayes' theorem. Starting with a dataset consisting of soil parameter measurements and the corresponding remote sensing data, it aims to quantify the spread of measurements with respect to the theoretical values, and it incorporates this information into the inversion algorithm. The differences between theoretical and experimental values are taken into account by introducing random variables not depending on soil parameters and representing the randomness that is not considered in the theoretical formula (used below) [6].

Starting with two quantities, the ratio of HH (Horizontal-Horizontal polarization) to VV (Vertical-Vertical polarization), L-band radar cross-section, represented by m, and that of HV (Horizontal-Vertical polarization) to VV, represented by n, we designate the random variable associated with m as Y_m and that with n as Y_n. If we denote the dielectric constant by e and the rms height of the surface element under consideration by h, then Y_m and Y_n can be represented as [4]

$$Y_m = f(Z_e, Z_h).\ M_1 \qquad (4)$$
$$Y_n = g(Z_e, Z_h).\ M_2 \qquad (5)$$

where,
Z_e is the random variable representing e, the dielectric constant,
Z_h is the random variable representing h, the rms height,
f, g are some functions of Z_e and Z_h to be determined

M_1, M_2 are perturbation random variables representing the remaining randomness in (m, n).

Now the conditional probability density function satisfies [5]

$$P(e, h|\ m, n) = P_{(Ze,\ Zr)}\ (e,h)\ .f(e,h)^{-1}.\ g(e, h)^{-1}\ P_{(M1,M2)}\ .\{m/f(e,h), n/g(e,h)\}.\ C \qquad (6)$$

where $P_{(Ze,\ Zr)}$ (e,h) denotes the *apriori* joint density function. The joint probability of any type (z_1, ..., z_n) corresponding to the variables or attributes Z_1, …, Z_n is computed by

$$P(z_1, \ldots, z_n) = \prod_{(i=1\ \text{to}\ n)} P(z_i|\ Z_i) \qquad (7)$$

where the values for $P(z_i|\ Z_i)$ correspond to the entries in the conditional probability table for Z_i.

Studies reveal that whenever the measured variable is the received power, M_1 and M_2 each are gamma (denoted by Γ) distributed and are independent of each other. Converging further, when the measured variables are ratios of received powers, each M_i is distributed like the ratio of the two corresponding mutually independent Γdistributions.

Bayesian model

Using the above Bayesian principles, a model is constructed as follows:

$$m = f(e,h)M_1 = [1-(2\theta/\pi)^{1/3\Gamma}.\exp(-kh)]^2 M_1 \qquad (8)$$
$$n = g(e,h)M_2 = 0.23\sqrt{\Gamma}[1-\exp(-kh)]M_2 \qquad (9)$$

where,
θ is the incidence angle(=23°)
k is the wave number (=1.1101 per cm for a frequency of 5.3 GHz)

$$\Gamma = [(1-\sqrt{e})/(1+\sqrt{e})]^2 \qquad (10)$$

This model was used to create plots of m, n in terms of e and h in MATLAB, where e was varied from 2 to 10 and h from 0.4 to 12 cm in steps of 0.5. Thus, a clear visualization of variations of e, h and σ (scattering coefficient- observed from SAR image)was obtained.

To obtain the expression only in terms on e, an assumption was made on h that h= average rms surface height=3.5 cm. Thus, e can be obtained from the expressions in terms of m and n. In other words, e was calculated in terms of the backscatter coefficient.

Determination of soil moisture using the Dielectric constant

Dielectric constant is a measure of how easy a medium can conduct electrical signal. Dry soil has lower dielectric constant than that of moist soil. There exists a complex relationship between dielectric constant e and soil moisture MC. The moisture count and the dielectric permittivity are correlated and do not depend

on the material properties. The relation between the moisture count and the dielectric permittivity can be described with a polynomial of third class to fit all three calibration data-sets. If E denotes the real part of e, then the relationship is given by eq. 12 [7]

$$MC=-5.3.10^{-2}+2.92.10^{-2}E-5.5.10^{-4}E^{2}+4.3.10^{-6}E^{3} \quad (11)$$

Error Analysis

At this point the known values of soil moisture from the field data are compared with the values obtained from the Bayesian model. The error in the values is calculated and the average error is calculated. The corrected soil moisture expression is obtained by incorporating the average error into the expression for soil moisture.

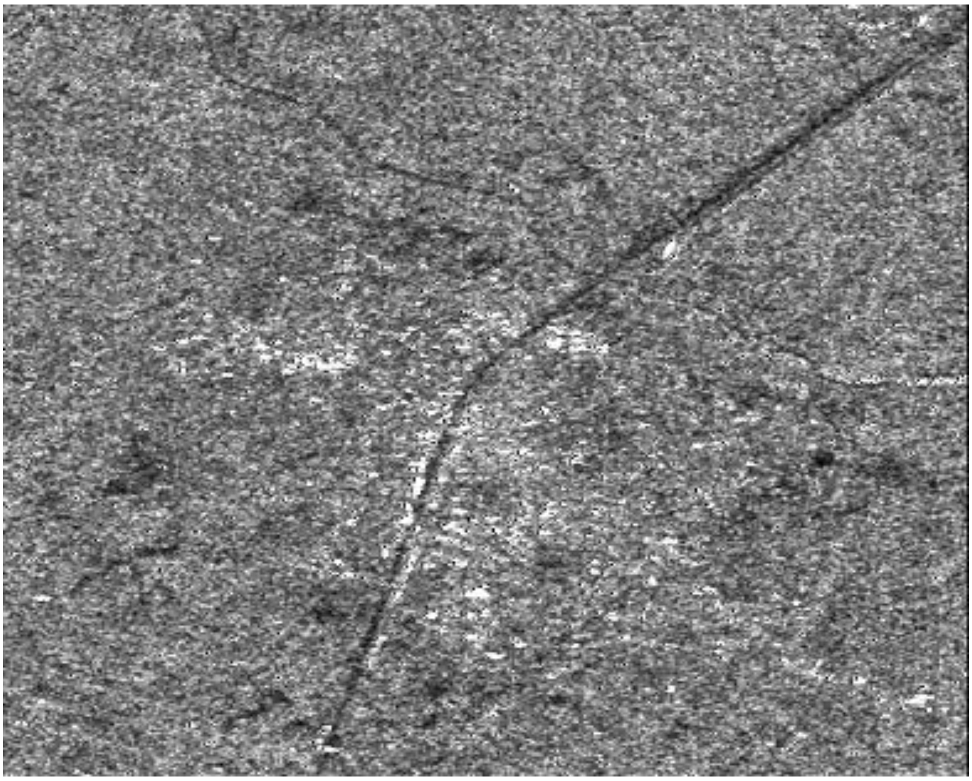

Fig. 1. ERS-2 SAR C band georeferenced image of Roorkee region of India (date 28th July 2003)

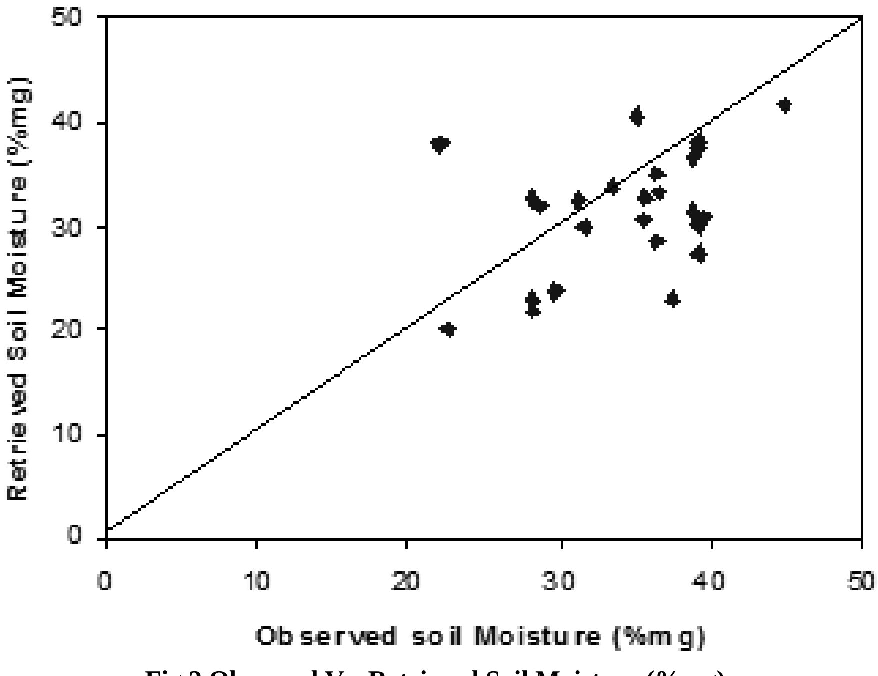

Fig.2 Observed Vs. Retrieved Soil Moisture (%mg)

Retrieval of soil moisture

Finally, soil moisture is retrieved by implementing the above approach.

RESULTS

The ERS-2 SAR C band image was used to find out the direct backscatter coefficient at various points on the geo-referenced image, which represents an area on the ground. This backscatter coefficient was used to obtain the values of dielectric constant at those points on the area using Bayesian Estimation Technique, assuming a constant surface rms height.

The relationship between the volumetric soil moisture and the dielectric constant gave us the corresponding values of soil moisture for those particular points on the surface. These were compared with the actual values of soil moisture obtained from the field data. The results are shown in Fig. 2.

CONCLUSION

Soil moisture is retrieved with Bayesian approach with ERS-2 data. Only assumption is that the roughness is kept constant.

Comparing with the field data it is found that the estimated values are closely related with the actually values from the field data. However, there is a certain amount of error in the retrieved soil moisture, which is due to the assumption of a constant rms surface height. Thus, some corrections can be applied to the model for better results, including topographical correction, vegetation correction and surface roughness correction. These will give us more accurate soil moisture maps for the area. These maps can be used for hydrologic modeling and other applications.

This Bayesian approach for inversion is a general method, which can be used to formulate useful relationships for various physical quantities of importance in different fields.

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